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Scale-dependent capital flows and systemic risk: Multifractal evidence from Mainland China–Hong Kong Stock Connect

Can-Zhong Yao *, Hao Jiang

School of Economics and Finance, South China University of Technology, Guangzhou, 510006, China

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ABSTRACT

This study examines the multifractal and asymmetric dynamics of cross-border capital flows under the Mainland China–Hong Kong Stock Connect system. Using asymmetric MF-DFA and MF-DCCA on daily data from 2016 to 2024, we document nonlinear scaling, directional asymmetry, and scale-dependent patterns in both capital flows and market returns. The results reveal a contrast between price dynamics and capital flows across market conditions: while return series tend to exhibit more compressed multifractal spectra in downward states, capital flows and their cross-market interactions display broader spectra, indicating greater dispersion in scaling behavior. In addition, differences between Northbound and Southbound channels suggest heterogeneous flow–return interactions across regimes and scales. These findings are robust across alternative detrending methods, and are further supported by shuffled and surrogate data diagnostics. Overall, the results highlight the importance of scale-dependent perspectives in understanding the interaction between capital flows and market dynamics in partially integrated financial systems.

1. Introduction

The growing integration of global financial markets has significantly heightened the importance of cross-border capital flows, particularly for emerging economies undergoing phased liberalization. China's Shanghai–Hong Kong Stock Connect (2014) and Shenzhen–Hong Kong Stock Connect (2016) exemplify this trend, establishing regulated channels for bidirectional equity investment between Mainland China and Hong Kong. These programs facilitate *Northbound* (NB) flows — foreign capital entering A-shares — and *Southbound* (SB) flows—Mainland investors purchasing Hong Kong–listed equities. Beyond improving market access, these channels provide a unique institutional setting for observing investor behavior and cross-market risk transmission under a controlled liberalization framework.

This study is motivated by a central economic question: *Do cross-border capital flows act as informative signals of systemic risk?* We further examine how this role varies across market states and investor types. While a substantial body of literature has examined the impact of capital flows on returns, volatility, and market efficiency, most studies focus on average effects or contemporaneous relationships. As a result, the dynamic, scale-dependent, and state-contingent informational role of capital flows — particularly during periods of market stress — remains insufficiently understood. To maintain a clear focus, this study centers on the informational role of capital flows in reflecting systemic risk. The analysis of behavioral asymmetries and cross-market interactions is treated as mechanisms through which this informational role may be revealed, rather than as separate research objectives.

Prior to the inception of the Stock Connect programs, Mainland China implemented a sequence of progressive financial liberalization measures, including QFII (2002), QDII (2006), and RQFII (2011). However, these earlier mechanisms primarily

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* Corresponding author.
E-mail address: yaocanzhong@scut.edu.cn (C.-Z. Yao).

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targeted institutional investors under strict regulatory constraints. In contrast, the Stock Connect programs represent a landmark policy innovation by enabling broader participation from both institutional and retail investors across markets. This structure not only enhances market integration but also introduces heterogeneous investor behavior and new channels of risk transmission.

The significance of NB and SB flows extends beyond facilitating market connectivity, as these channels fundamentally shape liquidity transmission, influence asset prices, and bear upon systemic resilience. Existing studies have documented several stylized facts, including asymmetries between inflows and outflows and differences between NB and SB flows. For example, NB flows are often interpreted as "smart money" driven by foreign institutional investors, whereas SB flows are more closely associated with domestic sentiment and retail participation. However, these findings are typically derived from linear or single-scale frameworks and provide limited insight into how such asymmetries evolve across different time scales or market conditions. Rather than re-characterizing these stylized facts, this study contributes by providing a mechanism-based and scale-dependent interpretation of these patterns. In particular, we interpret capital flows as risk-related signals whose informational content may vary across market states and fluctuation magnitudes. This perspective allows us to move beyond average relationships and examine how capital flows reflect underlying market fragility.

Methodologically, we employ asymmetric Multifractal Detrended Fluctuation Analysis (MF-DFA) and Multifractal Detrended Cross-Correlation Analysis (MF-DCCA). Importantly, the multifractal framework is not used as an end in itself, but as a tool to uncover scale-dependent and state-contingent dynamics in capital flows and their interaction with market returns. Unlike conventional approaches — such as dynamic correlations or copula models — that impose predefined dependence structures, multifractal analysis allows these relationships to emerge across different fluctuation magnitudes and time scales. At the same time, it is important to note that the economic interpretation of multifractal measures is not uniquely identified; the observed scaling properties may reflect a combination of behavioral heterogeneity, temporal dependence, and distributional features.

Guided by this framework, we examine daily NB and SB flows alongside the Shanghai Composite Index and the Hang Seng Index over the period 2016–2024. Our analysis focuses on three interrelated dimensions. First, we investigate whether capital flows exhibit multifractal scaling properties consistent with heterogeneous and state-dependent behavior. Second, we analyze directional asymmetries between inflows and outflows across different market conditions. Third, we examine the cross-market interaction between flows and returns to assess whether capital flows are systematically associated with channels of risk transmission.

The main findings reveal a distinctive pattern that we refer to as "structural inversion". During periods of market stress, asset price dynamics tend to become more homogeneous, while capital flows exhibit increased structural complexity and heterogeneity. This pattern is interpreted as an empirical regularity rather than a causal mechanism. In particular, it is consistent with the idea that the relative prominence of structural complexity shifts from prices to flows during stress periods, without implying a directional reallocation of informational content. Furthermore, we find that NB flows exhibit mean-reverting and externally driven characteristics, whereas SB flows reflect more behaviorally driven dynamics associated with domestic sentiment. Importantly, capital withdrawals — particularly at smaller scales — are associated with richer multifractal structures than large inflow episodes.

This study contributes to the literature in three ways. First, it provides a mechanism-based perspective linking heterogeneous investor behavior to scale-dependent multifractal dynamics in capital flows. Second, it introduces the concept of structural inversion as an empirical regularity that summarizes how complexity differs across prices and flows under market stress. Third, it offers new insights into the distinct roles of NB and SB channels, highlighting the scale-dependent and state-contingent nature of capital flow dynamics.

This paper positions itself as a structural characterization of cross-border capital flow dynamics under heterogeneous behavioral regimes. Rather than focusing solely on aggregate flow volumes or average correlations, we examine how the interaction between capital flows and returns evolves across scales and market states. In doing so, the paper moves beyond a re-characterization of established stylized facts by showing that capital flow dynamics exhibit state-dependent asymmetry, directional heterogeneity, and scale-specific informational content. These features imply that the informational role of capital flows is not constant, but varies with market conditions—particularly during withdrawal phases, when structural complexity becomes more pronounced.

Importantly, these findings should be interpreted within the institutional context of the Mainland China–Hong Kong Stock Connect system, which features distinct regulatory structures, investor compositions, and trading mechanisms. Caution is therefore warranted when generalizing these results to broader financial systems without additional supporting evidence.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature; Section 3 outlines the theoretical framework; Section 4 presents the methodological framework; Section 5 describes the data; Section 6 presents the empirical results; Section 7 discusses the economic interpretation and implications; and Section 8 concludes with policy implications.

2. Literature review

In the context of China's Stock Connect programs, capital flows operate through regulated channels linking the Mainland and Hong Kong stock markets, reflecting a *controlled liberalization* paradigm. These flows are shaped by cross-border investment behavior, informational frictions, and evolving regulatory frameworks. A growing body of literature has examined the implications of these programs from multiple perspectives, including market integration, investor behavior, corporate outcomes, and financial stability.

Early studies primarily focus on the impact of Stock Connect on market integration and liquidity. Evidence generally suggests that the program enhances cross-market connectivity and reduces segmentation. For example, Burdekin and Siklos (2018) document a narrowing of price disparities across markets, while Xie (2022) and Xu et al. (2020) report improvements in liquidity and reductions in price manipulation. However, subsequent research indicates that these effects are not uniform across time. In particular, Northbound flows may introduce short-term volatility and liquidity shocks, especially during the early stages of market liberalization (Wu & Ohk, 2023). More broadly, capital flow dynamics appear to be state-dependent: foreign investors may act as stabilizing agents through contrarian trading during periods of stress (Bing & Ma, 2021), while in other market conditions their behavior may shift toward pro-cyclical or trend-following patterns (He et al., 2024; Zhu, 2025).

Beyond market-level outcomes, the literature also documents the influence of cross-border capital flows on firm behavior. Foreign participation has been associated with improvements in corporate governance, ESG performance, and innovation, particularly among financially constrained firms (Chen et al., 2024; He et al., 2025b; Wang et al., 2023; Zhao et al., 2024). In addition, the program appears to encourage longer-term investment horizons, with more pronounced effects among privately owned firms with significant foreign shareholding (Zhao et al., 2024). Despite these improvements, persistent pricing anomalies — such as the A–H share premium — suggest that full market integration remains incomplete. Empirical evidence remains mixed, with some studies documenting a widening of the premium (Zhang et al., 2021), while others report a narrowing effect driven by cross-border demand and improved price parity (Pan & Chi, 2021). These differences are often attributed to information asymmetries and heterogeneous investor behavior (Huo & Ahmed, 2017; Pan & Chi, 2021; Yang et al., 2019; Yao & Li, 2023). At the same time, foreign participation has been shown to reshape herding dynamics by reducing information barriers and enabling more fundamentals-based trading strategies (Chen et al., 2024; Zhao et al., 2021).

The literature further considers the broader risk implications of Stock Connect. Some studies suggest that increased openness may raise exposure to systemic risk factors (Li et al., 2023), while others find evidence of reduced extreme downside risk and lower crash probability due to improved transparency and monitoring (Zhang et al., 2022). Nevertheless, during periods of market stress, Connect-eligible stocks remain sensitive to shocks. For instance, Bian et al. (2025) show that controlling for fire-sale risk during the 2015 market crash largely eliminates performance differences between eligible and non-eligible stocks. From a macro-financial perspective, foreign investors are also found to be highly sensitive to global conditions such as U.S. monetary policy and exchange rate movements, increasing the exposure of Mainland markets to external shocks (He et al., 2024). Overall, these findings suggest that Stock Connect simultaneously enhances market efficiency while introducing additional channels of global risk transmission.

A related strand of research examines the dynamic interaction between capital flows and asset returns. Using time-varying econometric frameworks, such as GARCH-based copulas, these studies document nonlinear and state-dependent dependence structures. For example, Yao and Jiang (2026) show that the relationship between Northbound capital flows and A-share returns evolves over time and depends on the information environment, with evidence of asymmetric and bidirectional feedback effects. These findings highlight that flow–return interactions cannot be adequately captured by static correlation measures, but instead vary across market conditions, time horizons, and external shocks. However, this literature primarily focuses on conditional dependence and tail behavior within parametric frameworks, and pays less attention to the scale-dependent structure of these interactions.

In parallel, a growing body of research applies multifractal methods to characterize financial market dynamics. Techniques such as MF-DFA provide evidence of nonlinear scaling, long-range dependence, and heterogeneous temporal structures in asset returns (Kantelhardt et al., 2002). Subsequent studies highlight that multifractality may arise from both temporal correlations and distributional properties (Bianchi, 2005). More recent work introduces asymmetric extensions to examine differences across market states, showing that scaling properties may vary between upward and downward regimes. Despite these advances, most multifractal studies focus on univariate dynamics and do not explicitly examine the interaction between capital flows and market returns.

Building on these strands, this study contributes by integrating multifractal analysis with the study of cross-border capital flows. Specifically, it extends the multifractal framework to a bivariate setting using MF-DCCA, allowing for the joint examination of capital flows and market returns. By incorporating both asymmetry and scale dependence, the analysis provides a more detailed characterization of how flow–return interactions vary across market states and fluctuation magnitudes. In addition, by comparing Northbound and Southbound channels, the study offers new evidence on heterogeneous dynamics within the Stock Connect system. Overall, this approach complements the existing literature on time-varying dependence by introducing a scale-dependent perspective on cross-market interactions.

2.1. Multifractal analysis in financial markets

Financial markets exhibit complex, non-linear dynamics that are not fully captured by traditional linear specifications. To address these features, recent studies have developed a range of advanced econometric frameworks. For instance, Dynamic Connectedness has been used to map network spillovers (Papathanasiou et al., 2025), while Dynamic Copula approaches capture time-varying tail dependence with or without regime switching (Samitas et al., 2020; Umar et al., 2020). Wavelet Coherence analysis has also been widely employed to examine multi-scale linkages and investment horizons (Kenourgios et al., 2011).

Within this broader landscape, multifractal analysis has emerged as a flexible framework for characterizing scale-dependent dynamics by identifying scaling relationships in financial time series. The most commonly used approach is Multifractal Detrended Fluctuation Analysis (MF-DFA), which can be extended to Multifractal Detrended Cross-Correlation Analysis (MF-DCCA) to study interactions between interdependent series across different time scales.

Early empirical applications of these techniques documented long-range dependence and scale-dependent fluctuations in asset returns. For example, Balcilar (2003b) identify multifractal properties in the Istanbul and Moscow stock markets, showing that persistence varies across volatility regimes. At the same time, the literature emphasizes the importance of methodological caution. Bianchi (2005) demonstrate that non-multifractal processes may appear multifractal in finite samples, highlighting the need for careful diagnostic testing. Similarly, Narayan and Sharma (2015) show that results can be sensitive to data frequency, implying that sampling choices affect the interpretation of scaling behavior. Methodological refinements, such as those proposed by Kristjanpoller and Bouri (2019), improve the estimation of the Hurst exponent under heavy-tailed distributions, thereby enhancing the reliability of MF-DFA in financial applications.

A large empirical literature applies MF-DFA across asset classes and generally finds that multifractal features become more pronounced during periods of market stress. For example, Aslam et al. (2021) show that in frontier markets, increased long-range dependence during crises may reduce diversification benefits. During the COVID-19 period, Ameer et al. (2023) report higher multifractality in BRICS and MSCI emerging markets, with particularly strong effects in Mainland China. Similar patterns are observed beyond equity markets: Naeem et al. (2022) find that both clean and traditional energy markets exhibit stronger multifractal features during global shocks, while Temel and Tuğay (2025) provide evidence consistent with the Fractal Market Hypothesis (FMH) across cryptocurrencies, commodities, and foreign exchange markets. Related findings across housing markets (Lee et al., 2018) and FinTech indices (Shrestha et al., 2023) further suggest that financial returns often exhibit scale-dependent structures that deviate from simple random walk behavior.

The multifractal framework also facilitates the analysis of cross-market linkages through MF-DCCA. This approach allows researchers to examine how two time series co-evolve across different fluctuation magnitudes, revealing dependencies that are not captured by standard correlation measures (Alvarez-Ramirez et al., 2009; Cao et al., 2013, 2014; Zhou, 2008). For example, Benlagha and Omari (2022) find that the relationships between stock, gold, and oil markets became more complex and scale-dependent during the COVID-19 period. Li et al. (2022) and Yao et al. (2021) document asymmetric cross-market interactions, showing that dependence structures differ between small and large fluctuations. More broadly, evidence from exchange rates, trading volume, and macroeconomic uncertainty (Gajardo et al., 2018; Guo et al., 2021; Kristjanpoller et al., 2020; Wang et al., 2023; Yang et al., 2019; Yao et al., 2020, 2026) indicates that cross-market linkages often vary across scales and market conditions, particularly during periods of systemic stress.

Multifractal measures have also been explored in forecasting and risk management contexts. For instance, Zhang et al. (2025) show that incorporating multifractal characteristics can improve the out-of-sample performance of return prediction models. These measures may also serve as indicators of changing market conditions, as increases in multifractal intensity are often observed during periods of instability. In risk management applications, multifractal-based approaches provide a more detailed characterization of volatility clustering and tail risk, which can improve Value-at-Risk (VaR) estimation. As noted by Benlagha and Omari (2022), such approaches are broadly consistent with the Adaptive Markets Hypothesis (AMH), as they allow market dynamics to evolve across regimes. At the same time, the interpretation of multifractal measures is not uniquely identified, as observed scaling patterns may also reflect distributional properties, aggregation effects, or heavy-tailed behavior rather than specific behavioral mechanisms.

In summary, the literature on MF-DFA and MF-DCCA highlights their usefulness in characterizing scale-dependent and non-linear dependencies in financial data. These approaches are particularly informative in environments characterized by market stress or partial integration, where traditional linear models may be insufficient. Rather than providing a single structural interpretation, multifractal techniques offer a flexible empirical framework for describing how market dynamics evolve across time scales and conditions.

3. Theoretical framework: Heterogeneous capital flows and multifractal scaling

3.1. *Economic intuition*

The dynamics of cross-border capital flows within the Stock Connect framework are shaped by the interaction of heterogeneous market participants, each characterized by distinct information sets, risk preferences, and regulatory constraints. Northbound (NB) flows primarily reflect the behavior of international institutional investors. The dynamics of these flows are closely associated with global risk conditions — such as fluctuations in the VIX — and portfolio rebalancing considerations, which may lead to periods of synchronized adjustments during episodes of global de-risking.

Conversely, Southbound (SB) flows are largely driven by domestic investors, whose allocation decisions are more closely related to local sentiment, wealth effects, and liquidity conditions in Mainland China. While the underlying drivers differ, both channels may exhibit common patterns during periods of market stress, when diverse signals can give rise to more coordinated capital reallocations.

This heterogeneity implies that capital flows cannot be adequately described by a representative-agent framework. Instead, they can be viewed as arising from a state-dependent multiplicative process, in which the aggregation of heterogeneous responses generates non-linear dynamics and scale-dependent fluctuations. In such settings, periods of moderate stress may increase heterogeneity across investors, while more extreme conditions may induce behavioral synchronization, leading to more homogeneous aggregate dynamics.

Within the framework of complex systems, these features are often associated with long-range dependence and multi-scale variability, which are characteristic of multifractal processes. However, it is important to note that the presence of multifractal scaling does not uniquely identify a specific economic mechanism; rather, it provides a flexible empirical representation of how fluctuations evolve across time scales. In this sense, multifractal analysis serves as a diagnostic tool for characterizing the structural complexity of capital flow dynamics, rather than a direct test of a single underlying behavioral model.

Table 1

Micro-economic foundations of state-dependent investor behavior and scaling dynamics.

Market state	Micro-economic mechanism	Behavioral and Statistical outcome
Downward ($m_t = -$)	Agents are subject to **binding margin constraints**, stop-loss protocols, and the reinforcement of pro-cyclical liquidity spirals (Brunnermeier & Pedersen, 2009).	Increased behavioral synchronization (herding), which may be associated with higher variability in scaling factors $\mathrm{Var}(\phi^{(-)})$ and more pronounced non-linear dynamics.
Upward ($m_t = +$)	Capital inflows are driven by heterogeneous "alpha-seeking" strategies and idiosyncratic expectations regarding growth potential.	More dispersed scaling factors, reflecting heterogeneous expectations and weaker synchronization across investors.

3.2. Heterogeneous-agent capital flow dynamics and scaling factors

This subsection formalizes the preceding economic intuition by developing a stylized heterogeneous-agent framework to motivate the emergence of state-dependent multifractal properties in cross-border capital flows. We define an aggregate capital flow series, $\mathcal{F}_t$, which represents the sum of net transactions executed by N heterogeneous investor groups:

$$\mathcal{F}_t = \sum_{i=1}^{N} w_i c_{i,t}, \tag{1}$$

where $c_{i,t}$ denotes the net capital adjustment of investor group i at time t, and w_i represents its relative market weight, with $\sum_{i=1}^{N} w_i = 1$.

Consistent with the literature on multiplicative cascade processes, individual agents are assumed to adjust their capital positions according to a regime-dependent multiplicative process:

$$c_{i,t} = \phi_{i,t}^{(m_t)} c_{i,t-1} + \varepsilon_{i,t}, \tag{2}$$

where $\phi_{i,t}^{(m_t)}$ denotes a state-dependent stochastic scaling factor governing the adjustment intensity of investor group i, $m_t \in \{+, -\}$ represents the prevailing market state (with $m_t = +$ indicating upward conditions and $m_t = -$ indicating downward conditions), and $\varepsilon_{i,t}$ is an idiosyncratic innovation term with zero mean.

To ensure system stability and preclude explosive divergence, we impose the condition $E[\ln \phi_{i,t}] \leq 0$, while allowing for intermittent fluctuations in $\phi_{i,t}^{(m_t)}$ that may generate clustered volatility and scale-dependent dynamics.

The central implication of this framework is that the statistical properties of the scaling factor $\phi_{i,t}^{(m_t)}$ may vary across market states due to differences in underlying micro-economic mechanisms. As summarized in Table 1, periods of market stress are associated with stronger synchronization across investors, whereas expansion phases tend to reflect more heterogeneous behavior.

Importantly, this framework does not imply a monotonic relationship between market stress and observed multifractal complexity. While moderate stress may increase heterogeneity across investors, more extreme conditions may induce stronger synchronization (e.g., herding or coordinated deleveraging), leading to more homogeneous aggregate dynamics and potentially narrower multifractal spectra.

This feature implies that regime-dependent reversals in multifractal behavior are theoretically admissible within the proposed framework, and that higher stress does not necessarily translate into greater multifractal dispersion.

In this sense, the model provides a conceptual motivation for state-dependent scaling behavior, rather than a uniquely identified structural mapping between micro-level mechanisms and multifractal measures. The multifractal properties observed in the data should therefore be interpreted as consistent with, but not exclusively determined by, the underlying heterogeneous-agent dynamics described above.

3.3. Emergence of multifractality

The aggregation of heterogeneous, state-dependent multiplicative processes may generate non-trivial scaling properties in the aggregate capital flow series. Consistent with the multifractal cascade literature, the qth order moments of fluctuations can be characterized by a scaling relationship with respect to the time horizon Δt:

$$E\left[|\mathcal{F}_{t+\Delta t} - \mathcal{F}_t|^q\right] \sim (\Delta t)^{\tau(q)}, \tag{3}$$

where $\tau(q)$ denotes the mass exponent function associated with moment order q. In a mono-fractal setting, $\tau(q)$ is linear in q, whereas deviations from linearity are typically interpreted as evidence of multifractal scaling.

Within the present framework, heterogeneity in the scaling factors $\phi_{i,t}^{(m_t)}$ may give rise to a spectrum of scaling exponents. Since the distributional properties of $\phi_{i,t}^{(m_t)}$ can vary across market states, the resulting scaling behavior may also exhibit regime dependence.

Importantly, this mechanism does not imply a unique mapping between micro-level heterogeneity and observed multifractal properties. Instead, it provides a conceptual channel through which state-dependent dynamics may be reflected in the scaling exponents. In this context, differences in multifractal characteristics across regimes can be interpreted as indicative of changes in the underlying balance between heterogeneous and synchronized behavior.

We refer to such regime-dependent variation in scaling behavior as "scaling symmetry breaking" in cross-border capital dynamics, understood as an empirical characterization rather than a strictly identified structural mechanism.

3.4. Propositions

Based on the stylized framework developed above, we formulate the following testable propositions to guide the empirical analysis:

Proposition 1 (*Endogenous Multifractality*). *Aggregate cross-border capital flows are expected to exhibit multifractal scaling properties, reflected in non-linear mass exponents $\tau(q)$. Such patterns may be consistent with the interaction of heterogeneous investor behaviors and multiplicative dynamics, although they are not uniquely attributable to these mechanisms.*

Proposition 2 (*Directional Asymmetry*). *If behavioral synchronization and the dispersion of scaling factors differ across market states — such that $Var(\phi^{(-)}) > Var(\phi^{(+)})$ — the multifractal spectrum in downward phases may be broader than in upward phases ($\Delta\alpha^{-} > \Delta\alpha^{+}$).*

However, this relationship is not necessarily monotonic. Under conditions of extreme stress, stronger synchronization may lead to more homogeneous aggregate dynamics, potentially reducing observed multifractal dispersion.

Proposition 3 (*Scale-Dependent Behavioral Dominance*). *The degree of directional asymmetry is expected to vary across time scales. When capital flows are primarily influenced by common exogenous shocks, asymmetries may diminish at larger temporal scales. Conversely, when flows are shaped by heterogeneous behavioral responses (e.g., herding or margin constraints), asymmetries may remain more pronounced at smaller fluctuation scales.*

3.5. Cross-market transmission and multifractal cross-correlations

The relationship between capital flows and asset returns, r_t, can be viewed as a system of interdependent and potentially non-linear interactions. To capture this intuition, we represent the joint dynamics in a stylized form:

$$\begin{cases} r_t = g(\mathcal{F}_{t-\ell}) + \eta_t, \\ \mathcal{F}_t = h(r_{t-\ell}, \sigma_t) + \xi_t, \end{cases} \tag{4}$$

where $g(\cdot)$ and $h(\cdot)$ denote general response functions that may incorporate non-linearities, ℓ represents a lag structure capturing delayed interactions, σ_t denotes time-varying market volatility, and η_t, ξ_t are stochastic disturbance terms.

The function $g(\mathcal{F})$ is assumed to allow for asymmetric price responses to capital flows. In particular, during periods of capital outflows ($\mathcal{F}_t < 0$), market conditions such as reduced liquidity may lead to stronger price sensitivity compared to inflow periods. This asymmetry can be interpreted as consistent with convex price responses under stressed liquidity conditions, although it is not imposed as a strict structural restriction.

Similarly, the function $h(r, \sigma_t)$ captures the possibility that capital flow responses to returns may vary across market conditions. While flows may respond gradually to moderate return fluctuations, more pronounced reactions may arise when returns fall below certain thresholds, reflecting changes in investor behavior under stress (e.g., deleveraging or risk reduction). These responses are treated as stylized representations rather than uniquely identified behavioral mechanisms.

Taken together, these interacting non-linearities provide a conceptual basis for understanding how cross-market dependencies may vary across regimes and fluctuation magnitudes. In particular, they may give rise to asymmetric and scale-dependent cross-correlations between capital flows and returns, which can be examined empirically using multifractal cross-correlation techniques.

Proposition 4 (*Asymmetric Cross-Correlations*). *If the sensitivity of capital withdrawals to adverse return shocks differs from the responsiveness of inflows to positive shocks, the resulting cross-market coupling may exhibit asymmetric scaling behavior. In such cases, the multifractal cross-correlation spectrum in downward market phases may differ from that in upward phases, potentially reflected in $\Delta\alpha_{xy}^{(-)} > \Delta\alpha_{xy}^{(+)}$.*

This relationship, however, is not necessarily monotonic, as stronger synchronization under extreme conditions may also reduce observed cross-correlation complexity.

3.6. Testable hypotheses

Drawing upon the stylized theoretical framework of state-contingent adjustments and heterogeneous investor behavior, we formulate the following testable hypotheses to guide the empirical analysis:

- **H1: Presence of Multifractality in Capital Flows.** Cross-border capital flows within the Stock Connect program are expected to exhibit multifractal scaling properties, reflected in non-linear scaling behavior across fluctuation magnitudes and time horizons. This hypothesis implies that the dynamics of capital flows may not be adequately described by a single Hurst exponent. Such patterns may be consistent with the interaction of heterogeneous trading strategies and heavy-tailed distributions of flow intensities, although they are not uniquely attributable to these mechanisms.
- **H2: Asymmetry in Multifractal Strength across Market States.** Downward market phases (characterized by capital withdrawals) are expected to display different multifractal characteristics compared to upward phases (capital inflows), potentially reflected in differences in the width of the singularity spectrum. From a conceptual perspective, such asymmetry may be associated with changes in behavioral responses — such as loss aversion or liquidity constraints — during market downturns. However, this relationship is not necessarily monotonic, as stronger synchronization under extreme stress may also reduce observed multifractal dispersion.
- **H3: Magnitude-Dependent Directional Asymmetry.** The degree of directional asymmetry is expected to vary with fluctuation magnitude. In particular, asymmetries may be more pronounced for small-scale fluctuations than for large-scale shocks. This reflects the possibility that large fluctuations are more closely associated with common macroeconomic factors, whereas smaller fluctuations may be more influenced by heterogeneous behavioral responses and idiosyncratic trading activity.
- **H4: Cross-Market Transmission under Different Market States.** Multifractal cross-correlations between capital flows and domestic stock returns are expected to vary across market states. In particular, withdrawal phases may be associated with stronger or more complex cross-market dependencies than inflow phases. This pattern can be interpreted as consistent with intensified feedback between price dynamics and capital flow adjustments during periods of market stress, although the empirical design does not directly identify a causal mechanism.
- **H5: Channel Heterogeneity (NB vs. SB Flows).** Northbound (NB) and Southbound (SB) flows are expected to exhibit different scaling behaviors across time scales. In particular, NB flows may display weaker directional asymmetry at longer horizons relative to SB flows. This difference may reflect the distinct investor compositions of the two channels, with NB flows more closely associated with globally synchronized institutional behavior, while SB flows may remain more sensitive to localized and sentiment-driven dynamics.

4. Methodology

In this study, the multifractal framework is not used as an end in itself, but as an empirical tool to characterize scale-dependent and state-contingent dynamics in capital flows that may not be captured by conventional econometric approaches.

4.1. Asymmetric MF-DFA

Multifractal Detrended Fluctuation Analysis (MF-DFA), introduced by Kantelhardt et al. (2002), provides a flexible framework for analyzing scaling properties in potentially non-stationary time series. Unlike conventional linear models or autocorrelation-based methods, MF-DFA allows the scaling behavior of a process to vary across fluctuation magnitudes and time scales, making it especially suitable for examining heterogeneous and state-dependent dynamics discussed in Section 3.

Let $\{x_t\}$ denote the time series of length N. The integrated profile is constructed as:

$$X(i) = \sum_{k=1}^{i}(x_k - \bar{x}), \quad i = 1, \ldots, N, \tag{5}$$

where $\bar{x}$ is the sample mean of $\{x_t\}$.

Divide $X(i)$ into $N_n = \lfloor N/n \rfloor$ non-overlapping segments of length n, and repeat the procedure from the opposite end to obtain a total of $2N_n$ segments.

For each segment v ($v = 1, \ldots, 2N_n$), fit a local second-order polynomial trend:

$$\hat{X}_v(i) = \alpha_v i^2 + \beta_v i + \gamma_v, \quad i = 1, \ldots, n, \tag{6}$$

where $\hat{X}_v(i)$ is the estimated trend. The detrended variance in each segment is then calculated as:

$$F^2(v,n) = \frac{1}{n}\sum_{i=1}^{n}\left[X[(v-1)n+i] - \hat{X}_v(i)\right]^2. \tag{7}$$

Segments are classified based on the slope coefficient β_v: $\beta_v > 0$ corresponds to upward regimes, and $\beta_v < 0$ corresponds to downward regimes. This classification serves as an empirical proxy for the theoretical market states discussed in Section 3.

Directional q-order fluctuation functions are defined as:

$$F_q^{dir}(n) = \left\{\frac{1}{M_{dir}}\sum_{v\in S_{dir}}\left[F^2(v,n)\right]^{q/2}\right\}^{1/q}, \tag{8}$$

where $dir \in \{up, down\}$, S_{dir} denotes the set of segments in each regime, and M_{dir} is the number of segments in that regime.

If long-range correlations are present, the fluctuation function follows the scaling relation:

$$F_q(n) \sim n^{H(q)}, \tag{9}$$

where $H(q)$ is the generalized Hurst exponent. Values of $H(q) \neq 0.5$ indicate deviations from uncorrelated behavior, while variation of $H(q)$ across q reflects scale-dependent dynamics.

The mass exponent $\tau(q)$ and singularity spectrum $f(\alpha)$ are obtained via the Legendre transform:

$$\tau(q) = qH(q) - 1, \quad \alpha = \frac{d\tau(q)}{dq}, \quad f(\alpha) = q\alpha - \tau(q). \tag{10}$$

The multifractal spectrum width is defined as:

$$\Delta\alpha = \alpha_{\max} - \alpha_{\min}, \tag{11}$$

which summarizes the dispersion of scaling exponents and may reflect heterogeneity, distributional properties, or aggregation effects.

4.2. Asymmetric MF-DCCA

To investigate cross-market interactions between capital flows and asset returns, we employ Asymmetric Multifractal Detrended Cross-Correlation Analysis (A-MF-DCCA) (Cao et al., 2014), which extends MF-DFA to a bivariate setting.

Let $\{x_t\}$ and $\{y_t\}$ denote two time series of length N. Construct their integrated profiles:

$$X(i) = \sum_{k=1}^{i}(x_k - \bar{x}), \quad Y(i) = \sum_{k=1}^{i}(y_k - \bar{y}), \quad i = 1, \ldots, N. \tag{12}$$

Divide each profile into $N_n = \lfloor N/n \rfloor$ segments, repeating from the opposite end to obtain $2N_n$ segments.

For each segment v ($v = 1, \ldots, 2N_n$), fit local second-order polynomial trends:

$$\hat{X}_v(i) = \alpha_{X_v} i^2 + \beta_{X_v} i + \gamma_{X_v}, \quad \hat{Y}_v(i) = \alpha_{Y_v} i^2 + \beta_{Y_v} i + \gamma_{Y_v}, \quad i = 1, \ldots, n, \tag{13}$$

where $\hat{X}_v(i)$ and $\hat{Y}_v(i)$ are the estimated trends.

The detrended fluctuations are:

$$\tilde{X}_v(i) = X[(v-1)n + i] - \hat{X}_v(i), \quad \tilde{Y}_v(i) = Y[(v-1)n + i] - \hat{Y}_v(i). \tag{14}$$

The detrended covariance in each segment is defined as:

$$F^2_{XY}(v, n) = \frac{1}{n}\sum_{i=1}^{n} \tilde{X}_v(i) \cdot \tilde{Y}_v(i). \tag{15}$$

Segments are classified into upward or downward regimes based on the slope of a reference series (e.g., stock returns), consistent with the empirical market states in Section 4.1.

The directional q-order fluctuation functions are then:

$$F^{dir}_{XY,q}(n) = \left\{ \frac{1}{M_{dir}} \sum_{v \in S_{dir}} \left[\mathrm{sgn}(F^2_{XY}(v,n))\, |F^2_{XY}(v,n)|^{q/2} \right] \right\}^{1/q}, \tag{16}$$

where $dir \in \{up, down\}$, S_{dir} denotes the set of segments in that regime, and M_{dir} is the number of segments.

If long-range cross-correlations exist, the fluctuation function satisfies:

$$F_{XY,q}(n) \sim n^{H_{XY}(q)}, \tag{17}$$

where $H_{XY}(q)$ is the generalized cross-correlation exponent.

4.3. Sources of multifractality: Shuffled and surrogate data procedures

To examine the potential sources of the detected multifractal properties — and to distinguish them from possible finite-sample or distributional effects as highlighted by Bianchi (2005) — we implement shuffled and surrogate data tests as diagnostic benchmarks. In the econophysics literature, these procedures are commonly used to assess whether multifractal features are associated with (i) temporal dependence (linear or non-linear memory) and/or (ii) heavy-tailed probability distributions.

The shuffling procedure involves randomly permuting the original time series $\{x_t\}$. This process removes temporal ordering and associated dependence structures while preserving the marginal distribution of the data. If the observed multifractality is primarily related to temporal correlations, the shuffled series is expected to display a substantially reduced multifractal signature, with the generalized Hurst exponent $H_{shuf}(q)$ approaching 0.5 across moment orders q.

The surrogate data are generated using the Iterative Amplitude Adjusted Fourier Transform (IAAFT) algorithm. This approach preserves the linear autocorrelation structure and the empirical distribution, while reducing non-linear dependencies. By comparing the multifractal spectrum width $\Delta\alpha$ of the original and surrogate series, we can assess whether non-linear features may contribute to the observed scaling behavior.

Following the diagnostic framework of Kantelhardt et al. (2002), the relative contributions to multifractality are evaluated through comparative scenarios summarized in Table 2.

The empirical results corresponding to these diagnostic scenarios are reported in Section 6.5. These comparisons provide indicative evidence on whether the observed multifractal characteristics are associated with temporal dependence and/or distributional properties, rather than being solely driven by simple linear correlations or static distributions.

It is important to emphasize that these procedures do not provide definitive identification of a single source of multifractality. Instead, they offer a diagnostic framework for assessing the relative importance of different contributing factors.

Table 2

Theoretical scenarios for multifractality diagnostics.

Scenario	Indicative source of multifractality	Expected empirical outcome
Case I	Long-range correlations (temporal dependence)	$\Delta\alpha_{shuf} \to 0$; $\Delta\alpha_{surr} \approx \Delta\alpha_{orig}$
Case II	Broad probability distribution (fat tails)	$\Delta\alpha_{surr} \to 0$; $\Delta\alpha_{shuf} \approx \Delta\alpha_{orig}$
Case III	Combined temporal and distributional effects	$\Delta\alpha_{orig} > \Delta\alpha_{shuf}$ and $\Delta\alpha_{orig} > \Delta\alpha_{surr}$

4.4. Methodological justification and comparative advantages

To further assess the suitability of the adopted framework, it is useful to compare the Asymmetric MF-DCCA approach with other commonly used econometric methodologies. Models such as the GARCH family, Vector Autoregression (VAR), and copula-based approaches provide complementary perspectives by capturing conditional heteroskedasticity, linear interdependence, and tail dependence, respectively. These approaches are well established in the literature and remain informative for analyzing financial market dynamics.

Within this broader context, the multifractal framework offers a non-parametric and scale-based perspective on time series behavior. Unlike parametric models that rely on specific functional forms, MF-DFA/DCCA allows for the characterization of scaling properties across different time horizons. This feature enables the examination of long-range dependence and potential variation in dynamics across fluctuation magnitudes, which may not be the primary focus of short-horizon models.

Second, while copula-based approaches are effective in modeling dependence structures at given horizons, the multifractal framework provides a way to examine how statistical dependencies may vary across time scales. This is particularly relevant in settings such as the Stock Connect program, where investors operate with heterogeneous time horizons and trading strategies.

Third, the asymmetric extension of the multifractal framework allows for the empirical comparison of upward and downward regimes. By conditioning on directional segments, the approach facilitates the examination of whether statistical properties differ across market states. In this sense, it provides an empirical lens through which patterns — such as directional asymmetry in scaling behavior — can be explored, rather than directly identifying specific structural mechanisms.

Importantly, the multifractal framework should be viewed as complementary to standard econometric approaches rather than as a substitute. While conventional models often focus on average dynamics or fixed dependence structures, the multifractal approach provides a descriptive characterization of how scaling behavior and dependence may vary across time scales and fluctuation magnitudes. In the context of cross-border capital flows, this perspective is useful for examining whether small-scale fluctuations and large-scale movements exhibit different statistical properties. Such differences may be consistent with heterogeneous behavioral responses or common shocks, although the framework itself does not uniquely attribute observed patterns to a single economic mechanism.

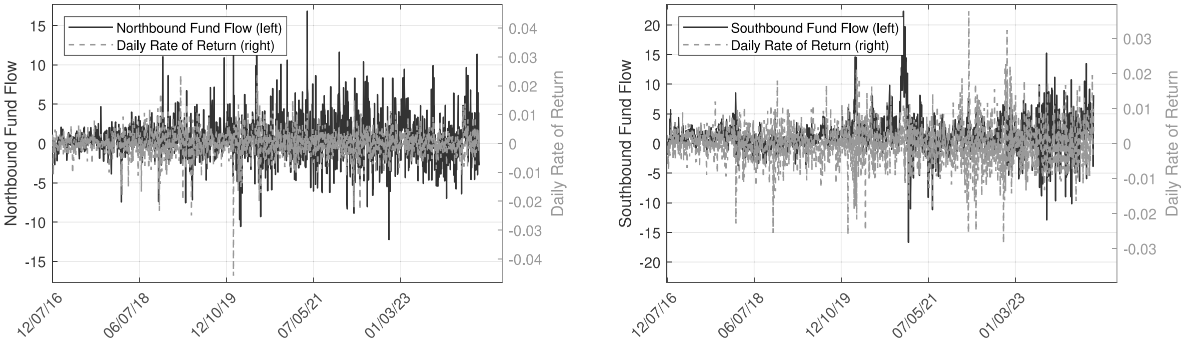
5. Data description and statistical tests

5.1. Data source and pre-processing

This study uses daily financial data from the Mainland–Hong Kong Stock Connect programs to explore the non-linear dynamics of cross-border capital flows and their potential implications for market integration. The decision to use daily frequency data is motivated by the theoretical mechanisms under investigation. Consistent with research on frequency dependence in financial dynamics (Narayan & Sharma, 2015), daily data provides a higher resolution that is crucial for capturing non-linear phenomena such as margin calls and liquidity-driven withdrawals, which may be obscured by lower-frequency aggregation (e.g., monthly data). This choice helps ensure that the multifractal estimates reflect true economic interactions, rather than being artifacts of sampling or temporal aggregation.

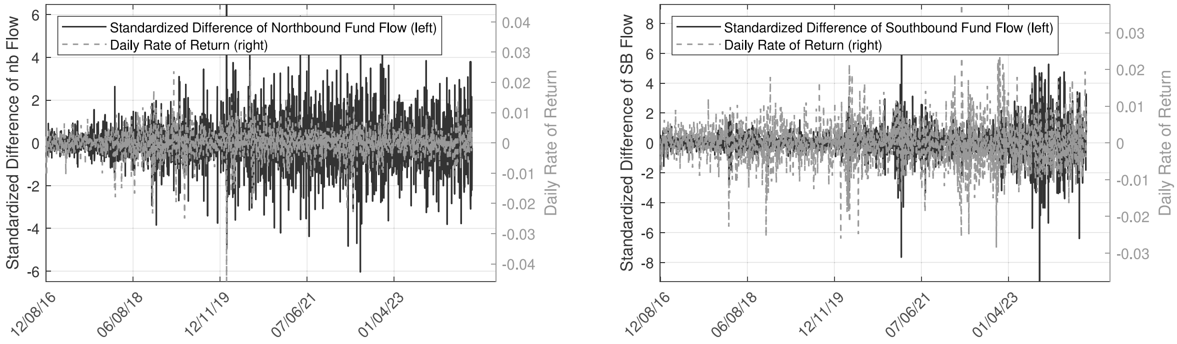
The analysis focuses on four key variables: the Shanghai Stock Exchange Composite Index (SSE), the Hang Seng Index (HSI), Northbound (NB) capital flows, and Southbound (SB) capital flows. These variables allow for an investigation into the bilateral interactions between the Mainland Chinese and Hong Kong equity markets, capturing both institutional and retail-driven capital movements (Figs. 1(a)–1(b)).

The temporal scope of the analysis spans from December 7, 2016, to May 13, 2024, providing a post-implementation window to examine the effects of Mainland China's "controlled liberalization" paradigm. Daily closing prices for the SSE and HSI, as well as the corresponding capital flow data, were obtained from official exchange disclosures and the Wind Financial Terminal. For empirical estimation, daily logarithmic returns (r_t) for the equity indices are calculated. To ensure stationarity and facilitate cross-market comparison, the Northbound and Southbound flow series are standardized and first-differenced. The stationarity diagnostics and the visual trajectories of the transformed series are presented in Figs. 1(c)–1(d), illustrating the stochastic behavior of the variables throughout the sampling period.



(a) Northbound flows and SSE returns (Levels).

(b) Southbound flows and HSI returns (Levels).



(c) Differenced Northbound flows and SSE returns.

(d) Differenced Southbound flows and HSI returns.

Fig. 1. Temporal trajectories of Northbound and Southbound capital flows and market returns.

Table 3
Descriptive statistics of the empirical time series.

	Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis	JB Statistic
Northbound	Return	−0.000004	0.00463	−0.04581	0.02412	−0.8182	8.5633	5402.89***
	Flow	0.51197	2.74443	−12.20673	16.81177	0.3462	2.7876	586.44***
Southbound	Return	−0.000043	0.00605	−0.02852	0.03775	0.1048	3.3364	794.40***
	Flow	1.39247	3.02426	−16.64881	22.29576	0.8961	6.9190	3631.19***

Note: JB denotes the Jarque–Bera statistic for normality. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard deviations are reported in parentheses where applicable.

5.2. Descriptive statistics and stylized facts

The visual evidence in Figs. 1(c) and 1(d) indicates that both the standardized first differences of capital flows and the logarithmic returns of the SSE and HSI fluctuate around a mean close to zero. A notable feature of these series is the presence of volatility clustering (or temporal heteroscedasticity), where periods of relatively low variability alternate with periods of large fluctuations. This pattern is widely documented as a stylized fact in financial time series and suggests the presence of temporal dependence in higher-order moments.

Such clustering behavior may be consistent with mechanisms discussed in Section 3.1, where shocks can propagate across markets and generate periods of heightened activity. However, this interpretation remains descriptive, as the observed patterns do not uniquely identify a specific underlying mechanism.

Table 3 reports the descriptive statistics for the capital flow series and market returns. The Jarque–Bera (JB) statistics reject the null hypothesis of normality for all variables at conventional significance levels, indicating deviations from a Gaussian distribution. These deviations are further reflected in the observed skewness and leptokurtic behavior (fat tails), suggesting the presence of extreme observations in the data.

Such distributional characteristics imply that the series exhibit features commonly associated with financial time series, including heavy tails and time-varying volatility. These properties provide empirical motivation for employing methods that can accommodate

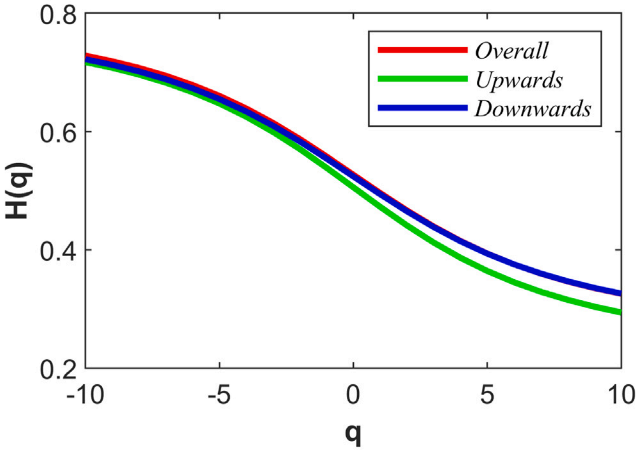


Fig. 2. Scaling exponents $H(q)$ as a function of the moment order q (range: $[-10, 10]$).

non-linear and scale-dependent behavior. In particular, the multifractal framework offers a way to characterize how statistical properties may vary across time scales and fluctuation magnitudes, without relying on a single scaling exponent.

Importantly, these descriptive results should be interpreted as indicative of complex dynamics rather than definitive evidence of a specific data-generating process. The subsequent multifractal analysis therefore serves as a complementary tool to further examine these features in a scale-dependent framework.

6. Empirical analysis of asymmetric multifractal dynamics

This section presents the empirical analysis corresponding to the theoretical propositions and hypotheses (H1–H5) developed in Section 3. The univariate MF-DFA analysis serves as a diagnostic step to characterize the scaling properties of individual series, while the main focus of the empirical investigation lies in the interaction between capital flows and market returns, as examined using the MF-DCCA framework.

To maintain a clear connection between the theoretical framework and the empirical design, the analysis proceeds in several steps. First, we examine the presence of multifractal scaling in capital flows and market returns (H1), assessing whether the data exhibit scale-dependent behavior beyond a single scaling exponent. Second, we investigate directional differences between upward and downward market states (H2), evaluating whether multifractal characteristics differ across regimes. Third, we analyze scale-dependent asymmetry (H3), distinguishing between small- and large-fluctuation regimes to examine whether statistical properties vary across different fluctuation magnitudes. Fourth, we examine cross-market interactions between capital flows and returns using the MF-DCCA framework (H4), focusing on whether cross-correlations differ across market states and time scales. Finally, we compare Northbound and Southbound channels (H5) to assess whether the two channels exhibit different scaling patterns, potentially reflecting differences in investor composition and market structure. This structure allows the empirical findings to be systematically related to the proposed hypotheses. Importantly, the results are interpreted as evidence on statistical patterns that are *consistent with* the theoretical framework, rather than as direct identification of specific underlying economic mechanisms.

6.1. Asymmetric multifractal properties of stock markets

This subsection presents empirical results related to H1 and H2 by examining the multifractal properties of stock returns and their potential directional asymmetries (see Fig. 2).

6.1.1. Shanghai stock market

Using the relationship in Eq. (10), we estimate the multifractal mass exponents $\tau(q)$ for the Shanghai Stock Exchange (SSE) Composite Index return series. The non-linearity observed in $\tau(q)$ (Fig. 3) suggests a deviation from mono-fractal scaling and is consistent with the presence of multifractal features in the data.

Following Koscielny-Bunde et al. (2006), we estimate the multifractal spectrum using the multiplicative cascade model. The parameters (a, b) are obtained via non-linear least squares, and the resulting multifractal strength $\Delta\alpha$ is reported in Table 4. These estimates allow for a comparison of scaling properties across the overall, upward, and downward market regimes.

The results indicate that the multifractal spectrum differs across market regimes. In particular, the estimated spectrum width in the downward phase ($\Delta\alpha^{-}$) is slightly smaller than that in the upward phase ($\Delta\alpha^{+}$).

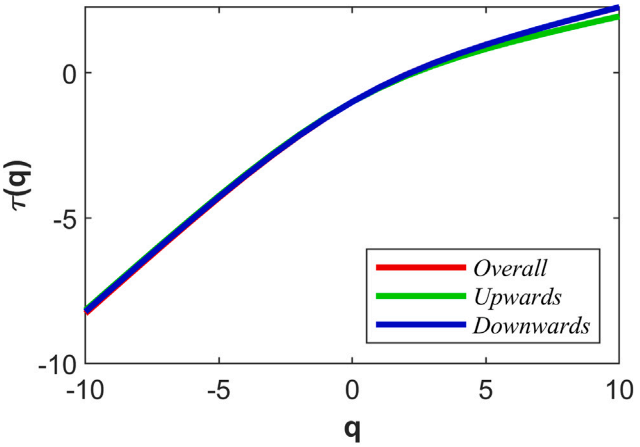


Fig. 3. Multifractal mass exponents $\tau(q)$ as a function of the moment order q (range: $[-10, 10]$).

Table 4
Estimated parameters and multifractal strength $\Delta\alpha$ based on the multiplicative cascade model.

Market regime	Parameter a	Parameter b	Multifractal strength $\Delta\alpha$
Overall	0.8540	0.5641	0.5983
Upward	0.8730	0.5683	0.6193
Downward	0.8537	0.5666	0.5914

This pattern contrasts with the baseline expectation in Proposition 2, which allows for stronger multifractal complexity under stress conditions. While the theoretical framework suggests that stress regimes may be associated with increased multifractal complexity, the empirical results here indicate that downturns may exhibit relatively narrower spectra, highlighting a potential tension between theoretical expectations and empirical evidence.

Importantly, the theoretical framework does not impose a strictly monotonic relationship between stress and multifractality. As discussed in Proposition 2, extreme stress conditions may induce stronger synchronization across investors, which can reduce dispersion in scaling behavior and lead to narrower spectra.

We therefore interpret these findings as suggestive rather than definitive, noting that they may reflect regime-dependent transitions between heterogeneous and synchronized dynamics. At the same time, alternative explanations — such as distributional effects or aggregation — cannot be ruled out (see Fig. 4).

Overall, the results provide evidence of directional differences in multifractal properties across market states. These differences are consistent with the broader framework of state-dependent dynamics, while also highlighting that empirical patterns may vary across regimes and are not fully determined by a single theoretical mechanism.

6.1.2. *Hong Kong stock market*

Using the A-MF-DFA framework, we examine the multifractal scaling behavior of the Hang Seng Index (HSI) across different fluctuation magnitudes and market directions. Figs. 5 and 6 present the generalized Hurst exponents $H(q)$ and the multifractal mass exponents $\tau(q)$ for the overall, upward, and downward return series.

For large-magnitude fluctuations ($q > 0$), the estimated $H(q)$ values for all three series are below 0.5. This pattern indicates anti-persistent scaling behavior, suggesting that large fluctuations tend to exhibit temporal reversals in direction over time, rather than implying a negative or contrarian relationship in a contemporaneous sense. The similarity of the curves across market states implies that large-scale dynamics are broadly comparable between upward and downward regimes.

In contrast, differences across market states are more evident for small-magnitude fluctuations ($q < 0$). The $H(q)$ curves for the overall and downward series are relatively close, whereas the upward series exhibits higher values in this range. This suggests that scaling properties at smaller fluctuation levels may differ across market directions.

Further evidence from the multifractal spectrum (Fig. 7 and Table 5) shows that the spectrum width differs across market regimes. The upward phase exhibits a wider spectrum ($\Delta\alpha = 0.5642$), while the downward phase shows a narrower spectrum ($\Delta\alpha = 0.3595$).

These findings are consistent with the possibility that multifractal characteristics vary across market states. In particular, the relatively narrower spectrum during downturns may reflect more homogeneous scaling behavior, whereas the broader spectrum in upward phases may be associated with greater heterogeneity in market dynamics.

However, these interpretations are not uniquely identified by the methodology. The observed differences may also be influenced by distributional properties or aggregation effects.

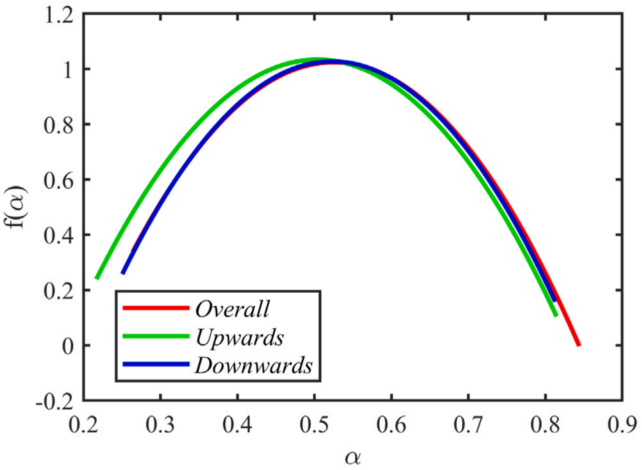


Fig. 4. Multifractal singularity spectra $f(\alpha)$ for different market regimes.

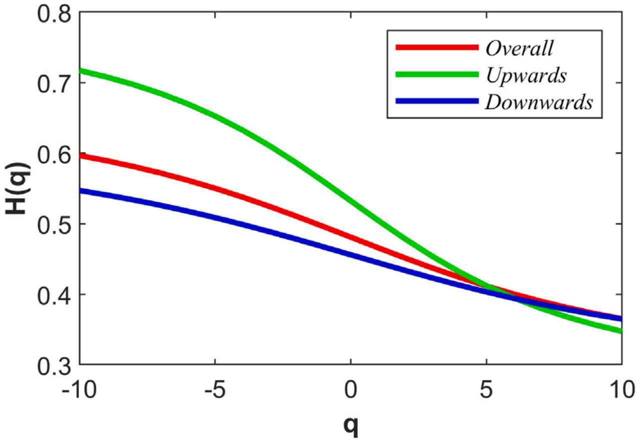


Fig. 5. Scaling exponents $H(q)$ as a function of the moment order q (range: $[-10, 10]$).

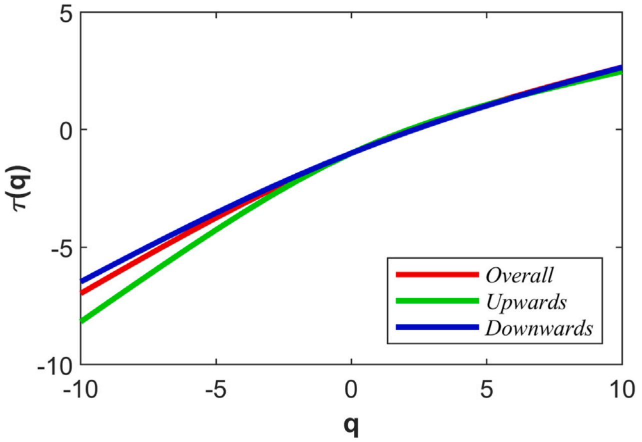


Fig. 6. Multifractal mass exponents $\tau(q)$ as a function of the moment order q (range: $[-10, 10]$).

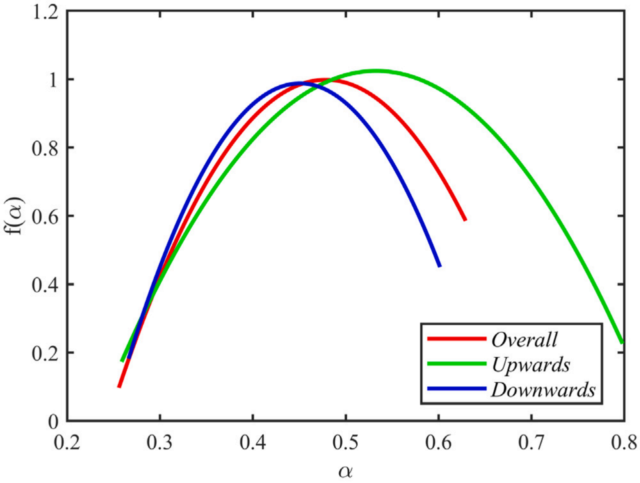


Fig. 7. Multifractal singularity spectra $f(\alpha)$ for the Hang Seng Index.

Table 5
Comparison of multifractal strength $\Delta\alpha$ for the Hong Kong market.

Market regime	Parameter a	Parameter b	Multifractal strength $\Delta\alpha$
Overall	0.8275	0.6203	0.4158
Upward	0.8407	0.5686	0.5642
Downward	0.8257	0.6436	0.3595

Overall, the results indicate the presence of directional differences in multifractal properties for the Hong Kong market. These patterns are consistent with the broader framework of state-dependent dynamics, while also suggesting that the relationship between market states and multifractal complexity may vary across markets and conditions.

6.2. *Asymmetric multifractal properties of capital flows*

This subsection examines the multifractal scaling properties of Northbound (NB) and Southbound (SB) capital flows, providing empirical evidence for H1–H3 regarding multifractality, directional asymmetry, and scale-dependent dynamics. Building on these results, we further compare the two channels to assess the presence of channel heterogeneity as proposed in H5. By contrasting the singularity spectra and Hurst exponents across market states, we show how differences in investor composition translate into distinct scaling behaviors. While the univariate multifractal analysis provides evidence of heterogeneous and state-dependent scaling behavior within each series, it does not directly address how capital flows and market returns interact. To capture this interplay, the subsequent analysis employs the MF-DCCA framework to examine the cross-market coupling between flows and returns, which constitutes the central focus of this study.

6.2.1. *Northbound fund flows: Asymmetric and scale-dependent dynamics*

Using the A-MF-DFA framework, we analyze the multifractal properties of Northbound capital flows into the Chinese Mainland market. Figs. 8 and 9 present the generalized Hurst exponents $H(q)$ and the mass exponents $\tau(q)$ for the overall series and its directional components.

Across the range of moment orders q, the estimated $H(q)$ values are below 0.5. This pattern indicates anti-persistent scaling behavior, suggesting that large fluctuations are more likely to be followed by reversals over time, rather than implying a negative or contrarian relationship in a contemporaneous sense. Such behavior is consistent with the absence of strong persistence in directional capital flow dynamics.

Differences across market states become more apparent when considering fluctuation magnitudes. For small-magnitude fluctuations ($q < 0$), the generalized Hurst exponents display a clear ordering: downward > upward > overall. This suggests that small-scale reductions in Northbound flows exhibit stronger temporal dependence compared to small-scale inflows.

For large-magnitude fluctuations ($q > 0$), the $H(q)$ curves across regimes are more closely aligned. This indicates that the scaling properties of large capital movements are relatively similar across market states, suggesting that large fluctuations may be associated with common factors affecting both inflows and outflows.

The multifractal spectrum analysis (Fig. 10 and Table 6) provides further evidence of regime-dependent differences. For higher singularity strengths ($\alpha > 0.2$), corresponding to small fluctuations, the spectra follow a similar ordering: downward >upward >overall. In contrast, for lower singularity strengths ($\alpha < 0.2$), the spectra are more closely aligned across regimes.

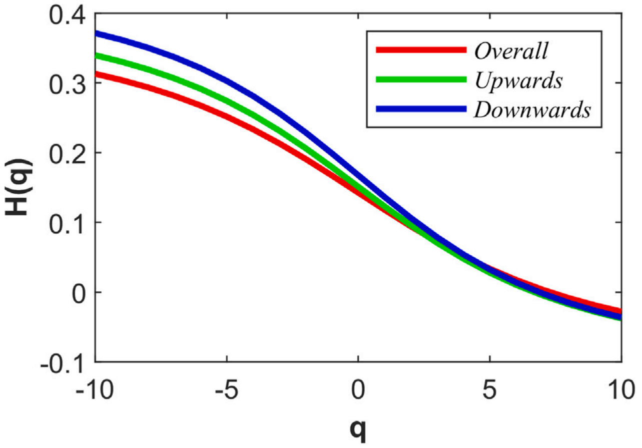


Fig. 8. Scaling exponents $H(q)$ as a function of the moment order q (range: $[-10, 10]$).

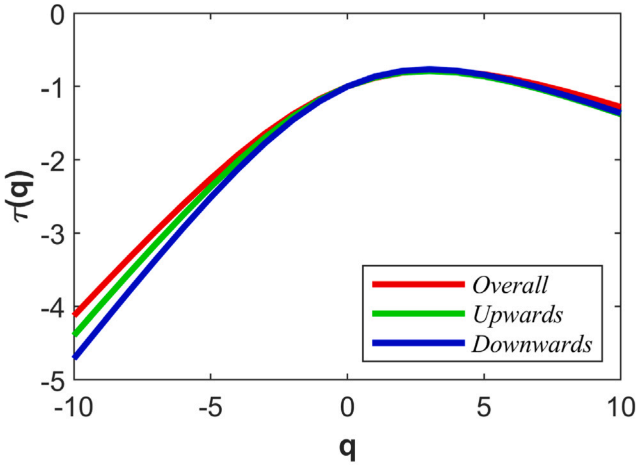


Fig. 9. Multifractal mass exponents $\tau(q)$ as a function of the moment order q (range: $[-10, 10]$).

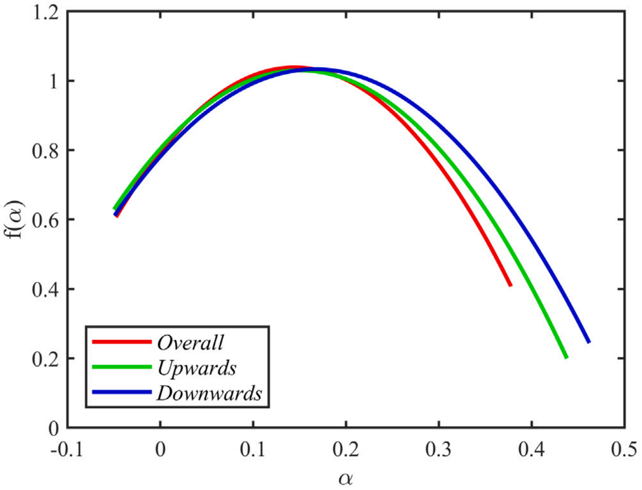


Fig. 10. Multifractal singularity spectra $f(\alpha)$ for Northbound capital flows.

Table 6
Estimated parameters and multifractal strength $\Delta\alpha$ for Northbound flows.

Market regime	Parameter a	Parameter b	Multifractal strength $\Delta\alpha$
Overall	1.0901	0.7529	0.5339
Upward	1.0981	0.7387	0.5719
Downward	1.0974	0.7224	0.6032

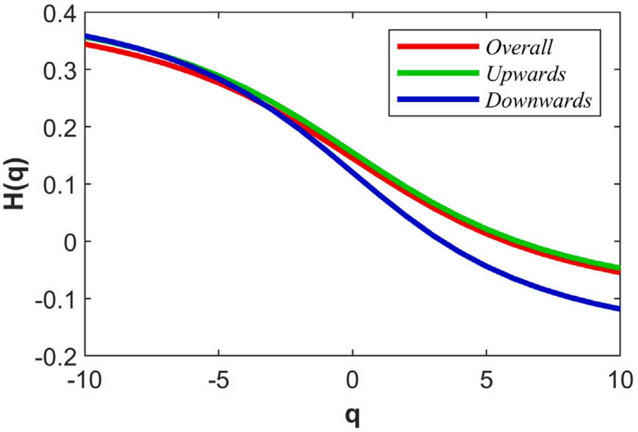


Fig. 11. Scaling exponents $H(q)$ as a function of the moment order q (range: $[-10, 10]$).

The comparison of spectrum widths shows that the downward component exhibits the largest $\Delta\alpha$, indicating greater dispersion in scaling exponents during withdrawal phases. This suggests that the statistical properties of capital flows differ across market states, particularly at smaller fluctuation scales.

From an economic perspective, these findings are consistent with the idea that capital flow dynamics may vary across regimes and fluctuation magnitudes. However, such interpretations are not uniquely identified by the methodology, and the observed patterns may also reflect distributional characteristics or aggregation effects.

Overall, the results indicate the presence of multifractality, directional asymmetry, and scale-dependent dynamics in Northbound capital flows. These patterns are consistent with the broader framework of state-dependent behavior, while highlighting that empirical findings should be interpreted as statistical regularities rather than direct evidence of specific underlying mechanisms.

6.2.2. Southbound fund flows: Asymmetric and heterogeneous scaling patterns

We next examine the multifractal properties of Southbound (SB) capital flows, representing capital movements from Mainland investors into the Hong Kong equity market. Figs. 11 and 12 present the generalized Hurst exponents $H(q)$ and the mass exponents $\tau(q)$ for the aggregate series and its directional components. The results indicate the presence of directional and scale-dependent differences that differ from the Northbound patterns discussed earlier.

For large-magnitude fluctuations ($q > 0$), the upward component is closely aligned with the aggregate curve and lies above the downward component. This pattern suggests that large-scale Southbound movements exhibit relatively similar scaling properties during inflow phases, while greater variation is observed during outflow phases.

At smaller fluctuation scales ($q < 0$), the upward, downward, and aggregate curves are more closely aligned. This indicates that small-scale adjustments in Southbound flows display broadly similar scaling behavior across market states.

The multifractal spectrum analysis (Fig. 13 and Table 7) provides additional evidence. The downward component exhibits the largest spectrum width ($\Delta\alpha = 0.6748$), exceeding both the upward ($\Delta\alpha = 0.5998$) and aggregate ($\Delta\alpha = 0.5945$) values.

The relatively broader spectrum observed during downward phases suggests greater dispersion in scaling exponents during withdrawal episodes. This indicates that the statistical properties of Southbound flows may differ across market states, particularly for larger fluctuations.

One possible interpretation is that withdrawal phases may be associated with more heterogeneous responses among investors, whereas inflow phases exhibit relatively more uniform dynamics. However, this interpretation is not uniquely identified by the methodology, and alternative explanations — such as distributional effects or aggregation — cannot be ruled out.

Comparing these findings with the Northbound results suggests that the two channels exhibit different scaling patterns. While Northbound flows display relatively symmetric behavior at large scales, Southbound flows exhibit more persistent differences across market states. These differences are consistent with the broader hypothesis of channel heterogeneity (H5), although the underlying economic mechanisms cannot be directly inferred from the multifractal analysis alone.

Overall, the results indicate the presence of multifractality, directional asymmetry, and scale-dependent dynamics in Southbound capital flows. These patterns are consistent with the broader framework of state-dependent behavior, while highlighting that empirical findings should be interpreted as statistical regularities rather than direct evidence of specific underlying mechanisms.

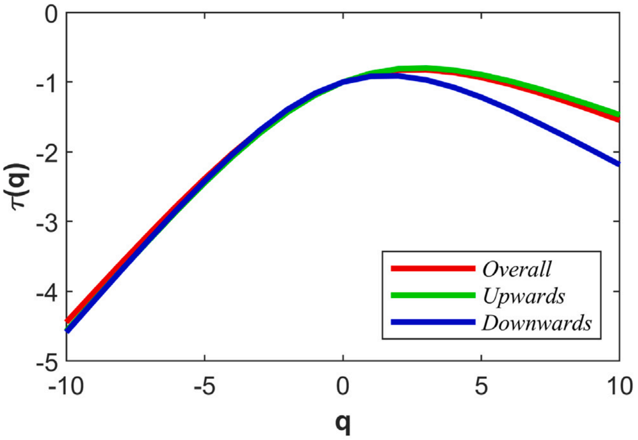


Fig. 12. Multifractal mass exponents $\tau(q)$ as a function of the moment order q (range: $[-10, 10]$).

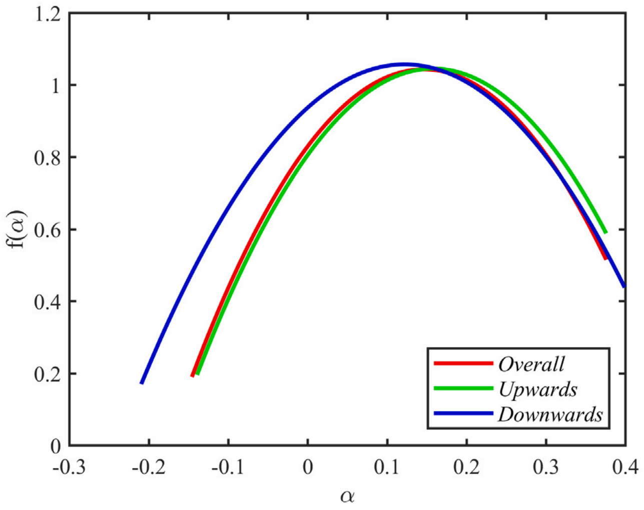


Fig. 13. Multifractal singularity spectra $f(\alpha)$ for Southbound capital flows.

Table 7
Estimated parameters and multifractal strength $\Delta\alpha$ for Southbound flows.

Market regime	Parameter a	Parameter b	Multifractal strength $\Delta\alpha$
Overall	1.1113	0.7360	0.5945
Upward	1.1056	0.7295	0.5998
Downward	1.1625	0.7282	0.6748

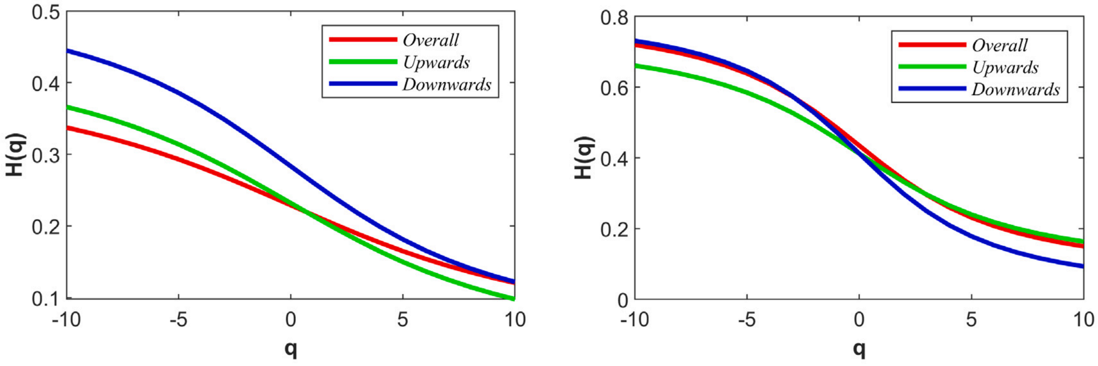
6.3. Asymmetric cross-correlations between capital flows and market indices

This subsection extends the analysis to a bivariate setting using the Asymmetric MF-DCCA framework to examine scale-dependent and directional cross-correlations between capital flows and market returns. The analysis focuses on whether cross-correlations differ across market states and fluctuation magnitudes, and whether such patterns vary between Northbound and Southbound channels.

6.3.1. Dynamic coupling: Northbound flows and the Shanghai composite index (SSE)

Based on the MF-DCCA methodology described in Section 4.2, we examine the cross-correlations between Northbound (NB) capital flows and the SSE Composite Index. Figs. 14(a)–14(b) and 15(a)–15(b) present the generalized cross-correlation exponents $H_{xy}(q)$ and the corresponding multifractal spectra for both Northbound–SSE and Southbound–HSI pairs.

Across market regimes, the estimated cross-correlation exponents $H_{xy}(q)$ are generally below 0.5. This pattern indicates anti-persistent cross-correlation behavior, suggesting alternating co-movements over time at certain scales, rather than implying a stable



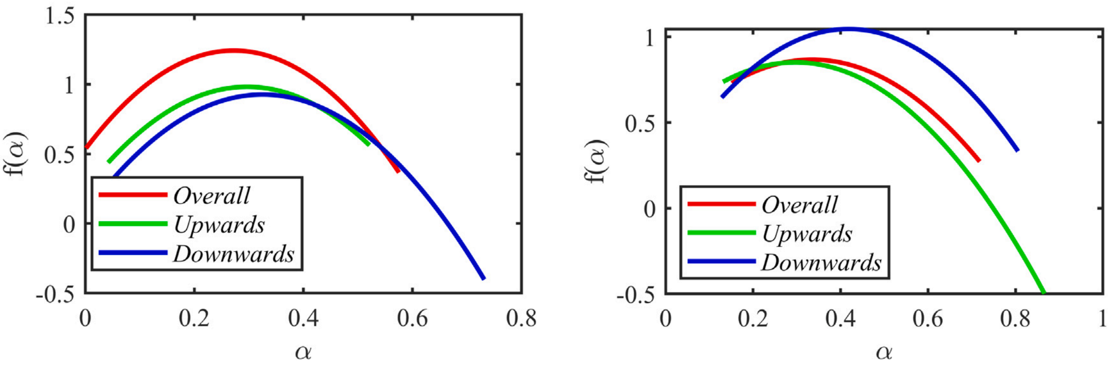
(a) NB flows and SSE returns. (b) SB flows and HSI returns.

Fig. 14. Generalized cross-correlation exponents $H_{xy}(q)$ as a function of the moment order $q \in [-10, 10]$.

Table 8

Multifractal cross-correlation strength $\Delta\alpha$ based on the multiplicative cascade model.

Correlation pair	Market regime	Parameter a	Parameter b	Spectrum width $\Delta\alpha$
NB flows & SSE index	Overall	0.9799	0.7430	0.3993
	Upward	0.9974	0.7270	0.4562
	Downward	0.9822	0.6874	0.5149
SB flows & HSI index	Overall	0.9656	0.5669	0.7683
	Upward	0.9562	0.5906	0.6951
	Downward	1.0044	0.5622	0.8372



(a) NB flows and SSE returns. (b) SB flows and HSI returns.

Fig. 15. Multifractal singularity spectra $f(\alpha)$ for the cross-correlation pairs.

negative relationship between capital flows and market returns. It is important to note that this reflects scale-dependent temporal dependence rather than a uniform sign of contemporaneous correlation between the two series.

These findings differ from simple contemporaneous correlation measures often discussed in the literature (e.g., "smart money" effects), highlighting that the relationship between flows and returns may vary across time scales and fluctuation magnitudes.

Directional differences are observed when separating upward and downward regimes. The downward component is consistently above the upward and aggregate components across q, indicating stronger cross-correlation in downward states. This suggests that the statistical coupling between flows and returns may be more pronounced during withdrawal phases.

Scale-dependent differences further refine this pattern. For small fluctuations ($q < 0$), the downward component remains the highest, while the upward component lies closer to the aggregate. For large fluctuations ($q > 0$), the upward component declines relative to the others, indicating weaker cross-correlation during large inflow episodes.

The multifractal spectrum analysis (Fig. 15(a) and Table 8) provides additional evidence. The downward regime exhibits the largest spectrum width ($\Delta\alpha = 0.5149$), followed by the upward and aggregate regimes. This indicates greater dispersion in scaling exponents during downward states, suggesting higher heterogeneity in cross-correlation structures across scales.

Table 9
Synthesis of empirical findings and relation to the theoretical framework.

Dimension	Stock returns	Capital flows (NB/SB)	Cross-correlations
Spectrum width	$\Delta\alpha^{(+)} > \Delta\alpha^{(-)}$	$\Delta\alpha^{(-)} > \Delta\alpha^{(+)}$	$\Delta\alpha^{(-)} > \Delta\alpha^{(+)}$
Interpretation	Downward states are associated with narrower spectra.	Withdrawal phases exhibit broader spectra.	Downward regimes display higher dispersion in cross-correlation structure.
Large-scale dynamics	Approximately symmetric across states.	NB: relatively symmetric/SB: asymmetric.	Directional differences across regimes.
Functional perspective	Price dynamics reflect aggregate outcomes.	Flow dynamics vary across regimes and scales.	Cross-correlations differ across states and fluctuation magnitudes.

Overall, the results indicate that cross-correlations between capital flows and market returns vary across market states and fluctuation magnitudes. In particular, downward regimes are associated with stronger and more heterogeneous cross-correlation patterns.

These findings are consistent with the broader framework of state-dependent dynamics. A similar pattern is observed for the Southbound–HSI pair (Figs. 14(b) and 15(b)), where directional differences and scale-dependent variations in cross-correlation structure are also evident, although the magnitude and dispersion of the multifractal spectrum differ across channels.

It is important to note that the MF-DCCA approach captures scale-dependent statistical dependence rather than causal transmission mechanisms. Accordingly, the observed patterns should be interpreted as descriptive features of the data. Alternative explanations — such as distributional characteristics or aggregation effects — may also contribute to the observed results.

6.3.2. Dynamic coupling: Southbound investment flows and the Hang Seng Index (HSI)

We next examine the multifractal cross-correlations between Southbound (SB) investment flows and the Hang Seng Index (HSI) using the MF-DCCA framework. Figs. 14(b) and 15(b), together with the parameter estimates in Table 8, indicate directional and scale-dependent differences in cross-correlation structure across market regimes.

For small-magnitude fluctuations ($q < 0$), the estimated cross-correlation exponents $H_{xy}(q)$ exceed 0.5. This pattern suggests persistent cross-correlation behavior, indicating that fluctuations in Southbound flows and the HSI tend to move in the same direction at these scales. The downward and aggregate components are closely aligned and lie above the upward component, suggesting relatively stronger cross-correlation during withdrawal phases at smaller fluctuation levels.

In contrast, for large-magnitude fluctuations ($q > 0$), the cross-correlation exponents fall below 0.5, indicating anti-persistent behavior. In this regime, the upward and aggregate components are closely aligned and lie above the downward component, suggesting relatively stronger cross-correlation during inflow phases at larger fluctuation scales.

The multifractal spectrum analysis provides additional evidence. The downward component exhibits the largest spectrum width ($\Delta\alpha = 0.8372$), followed by the aggregate ($\Delta\alpha = 0.7683$) and upward ($\Delta\alpha = 0.6951$) components. This indicates greater dispersion in scaling exponents during withdrawal phases, suggesting higher heterogeneity in cross-correlation structures across scales.

Overall, the results indicate that the cross-correlation between Southbound flows and the HSI varies across both market states and fluctuation magnitudes. In particular, withdrawal phases are associated with stronger and more heterogeneous cross-correlation patterns at smaller scales, while inflow phases exhibit relatively stronger cross-correlation at larger fluctuation levels.

These findings are consistent with the broader framework of state-dependent dynamics. However, it is important to note that the MF-DCCA approach captures scale-dependent statistical dependence rather than causal mechanisms. Accordingly, the observed patterns should be interpreted as descriptive features of the data, and alternative explanations — such as distributional characteristics or aggregation effects — cannot be ruled out.

6.4. Synthesis of empirical findings and relation to the theoretical framework

To provide an integrated view of the empirical findings, Table 9 summarizes the main patterns across stock returns, capital flows, and their cross-market interactions.

As shown in Table 9, the results indicate a consistent contrast across domains. While downward market states are associated with narrower multifractal spectra in returns, they correspond to broader spectra in capital flows and cross-correlations. This suggests that scaling properties differ across dimensions and may shift across market conditions.

These patterns are consistent with the broader framework of state-dependent dynamics developed in Section 3. In particular, the presence of multifractality in both flows and returns relates to H1, while the observed directional and scale-dependent differences correspond to H2 and H3. The cross-correlation results further indicate that interactions between flows and returns vary across regimes and fluctuation magnitudes, in line with H4 and H5.

Importantly, these findings should be interpreted as evidence of statistical regularities that are consistent with the proposed framework, rather than as direct validation of specific underlying mechanisms. The MF-DFA and MF-DCCA approaches capture scale-dependent dependence structures, but do not provide identification of causal processes. Therefore, alternative explanations — such as distributional properties or aggregation effects — may also contribute to the observed patterns.

Table 10
DFA-based robustness tests: Shuffled and surrogate comparisons.

Series type	Original $\Delta\alpha$	Shuffled $\Delta\alpha_{shuf}$	Surrogate $\Delta\alpha_{surr}$	Indicative source
SSE index (Mainland)	0.5983	0.3744	0.4668	Temporal/Non-linear
HSI index (Hong Kong)	0.4158	0.4615	0.4024	Distributional
Northbound (NB) flows	0.5339	0.4034	0.3854	Temporal/Non-linear
Southbound (SB) flows	0.5945	0.5211	0.5675	Mixed Dynamics

Table 11
MF-DCCA robustness tests for flow–return interactions.

Cross-correlation pair	Original $\Delta\alpha$	Shuffled $\Delta\alpha_{shuf}$	Surrogate $\Delta\alpha_{surr}$
NB flows & SSE index	0.3995	0.7213	0.6469
SB flows & HSI index	0.7684	0.7468	0.8266

6.5. *Sources of multifractality: Shuffled and surrogate diagnostics*

To examine the potential sources of the observed multifractality, we implement shuffled and surrogate data tests. In the econophysics literature, these procedures are commonly used to assess whether multifractal properties are associated with long-range temporal correlations or distributional characteristics.

Specifically, the shuffled series is constructed by randomly permuting the original observations, thereby removing temporal correlations while preserving the marginal distribution. In contrast, the surrogate series, generated via the Phase Randomization (PR) method, retains the linear autocorrelation structure but reduces nonlinear dependencies. By comparing the multifractal spectrum width ($\Delta\alpha$) across the original, shuffled, and surrogate series, we assess the relative contribution of these components.

Table 10 reports the results for the univariate analysis. For the Shanghai market (SSE) and Northbound (NB) flows, the spectrum width of the original series exceeds that of both shuffled and surrogate counterparts. This pattern suggests that temporal dependence and nonlinear effects may contribute to the observed multifractality.

In contrast, for the Hong Kong market (HSI), the spectrum width of the original series is comparable to that of the surrogate series and lower than that of the shuffled series. This pattern is consistent with a stronger role for distributional properties. Southbound (SB) flows display a mixed pattern, indicating that both distributional and temporal components may be relevant.

Table 11 presents the corresponding MF-DCCA results. For the Northbound channel (NB & SSE), the original cross-correlation spectrum is narrower than those of the shuffled and surrogate series. This suggests that the observed cross-correlation structure may be influenced by temporal organization that is disrupted by randomization.

In contrast, for the Southbound channel (SB & HSI), the spectrum width remains relatively large across all specifications, indicating that multifractal cross-correlation patterns persist under both shuffling and surrogate transformations. This suggests that multiple factors may contribute to the observed structure.

Overall, these results indicate that the observed multifractality is associated with a combination of temporal dependence, nonlinear effects, and distributional characteristics, with their relative importance varying across markets and capital flow channels. These tests provide indicative evidence on potential sources, but do not allow for definitive identification of underlying mechanisms.

6.6. *Robustness checks: Alternative detrending methods*

To further assess the robustness of the empirical findings, we re-estimate the multifractal cross-correlation properties using alternative detrending methods. In particular, we employ the MF-X-DMA approach with different parameter settings ($\theta = 0, 0.5, 1$), and compare the results with those obtained from the MF-DCCA framework. This procedure is motivated by potential methodological differences, as alternative detrending schemes may affect the estimated scaling behavior.

Figs. 16 and 17 present the results for the Shanghai (NB flows and SSE returns) and Hong Kong (SB flows and HSI returns) markets, respectively. Across both markets, the generalized Hurst exponents $h_{xy}(q)$ exhibit a consistent decreasing pattern with respect to q under all methods, indicating stable multifractal scaling behavior. Although the MF-DCCA estimates are slightly higher in magnitude for extreme negative q values — particularly in the Hong Kong case — the overall trajectories remain highly comparable.

A similar consistency is observed in the mass exponent functions $\tau_{xy}(q)$. As shown in Figs. 16(b) and 17(b), all methods produce nonlinear $\tau_{xy}(q)$ curves, which is consistent with multifractal scaling. Importantly, the curvature and relative positioning of these curves are broadly similar across MF-X-DMA and MF-DCCA, suggesting that the detected scaling structure is not sensitive to the choice of detrending method.

The multifractal spectra $f_{xy}(\alpha)$ further support this observation. In both Figs. 16(c) and 17(c), the spectra obtained from different methods exhibit similar shapes, peak positions, and widths. While minor quantitative differences exist — particularly in the right tail of the Hong Kong spectrum — the overall spectrum width ($\Delta\alpha$) and asymmetry patterns remain stable across methods. Compared with the MF-X-DMA results, the MF-DCCA method tends to produce slightly wider multifractal spectra, especially in the Hong Kong case. This difference likely reflects methodological distinctions in detrending procedures, leading to variations in how cross-scale fluctuations are captured, rather than indicating fundamentally different dependence structures.

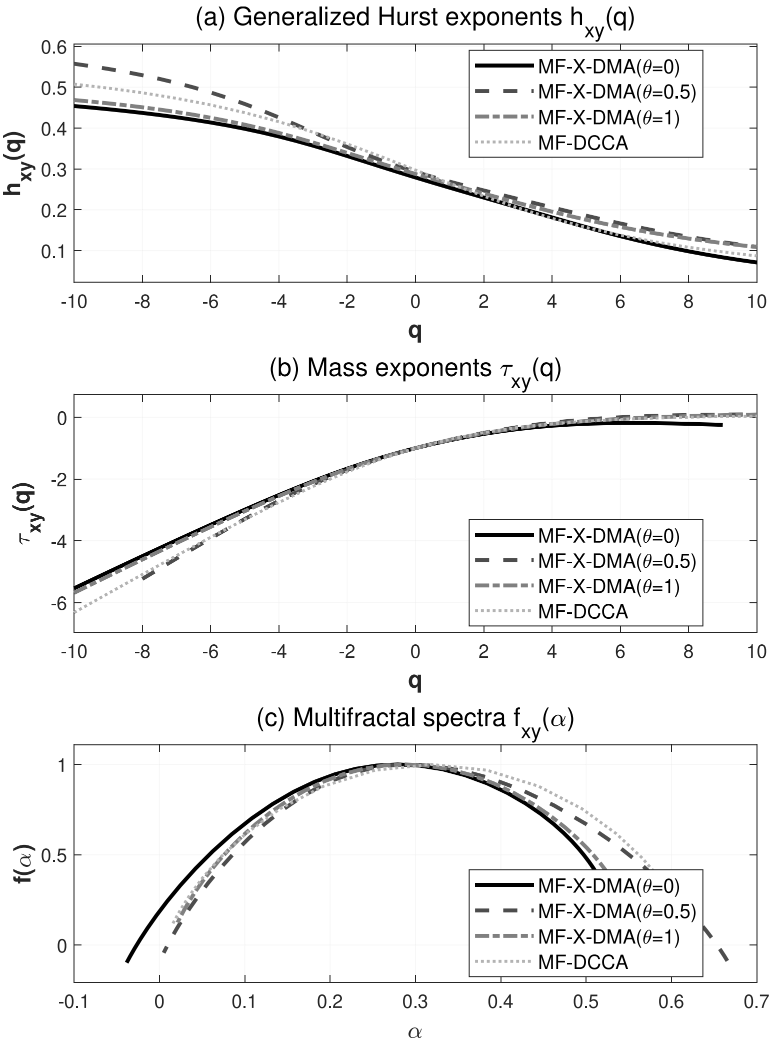


Fig. 16. Robustness analysis for the Shanghai market (NB flows and SSE returns). Panel (a) shows the generalized Hurst exponents $h_{xy}(q)$, panel (b) presents the mass exponents $\tau_{xy}(q)$, and panel (c) reports the multifractal spectra $f_{xy}(\alpha)$, obtained using MF-X-DMA ($\theta = 0, 0.5, 1$) and MF-DCCA methods.

Taken together, these results indicate that the main empirical patterns — such as the presence of multifractal cross-correlations and the observed directional and scale-dependent differences — are robust to the choice of detrending algorithm. The consistency across MF-DCCA and MF-X-DMA suggests that the findings are not driven by a specific estimation approach, but instead reflect stable and intrinsic features of the underlying cross-market dynamics.

7. Discussion

The empirical findings presented in this study highlight notable differences between the internal dynamics of individual markets and their cross-market interaction patterns. While the MF-DFA results indicate persistent multifractal behavior and nonlinear heterogeneity within each market, the MF-DCCA analysis suggests that cross-market correlations are less stable across scales. This contrast indicates that the complex return dynamics observed in the "Connect" markets are largely characterized by within-market scaling structures, while cross-market interactions vary across conditions.

The absence of persistent cross-scale MF-DCCA patterns suggests that interactions between the Mainland and Hong Kong markets may not exhibit uniform dependence across all time scales. Instead, cross-market relationships appear to vary across fluctuation regimes, becoming more pronounced under certain conditions. This interpretation is consistent with the broader framework of state-dependent dynamics, in which interactions between markets may differ across market states rather than remaining constant.

This pattern is observed consistently across the range of temporal horizons considered in the analysis. The coexistence of strong multifractality within individual markets and more variable cross-market coupling suggests that domestic dynamics and cross-market

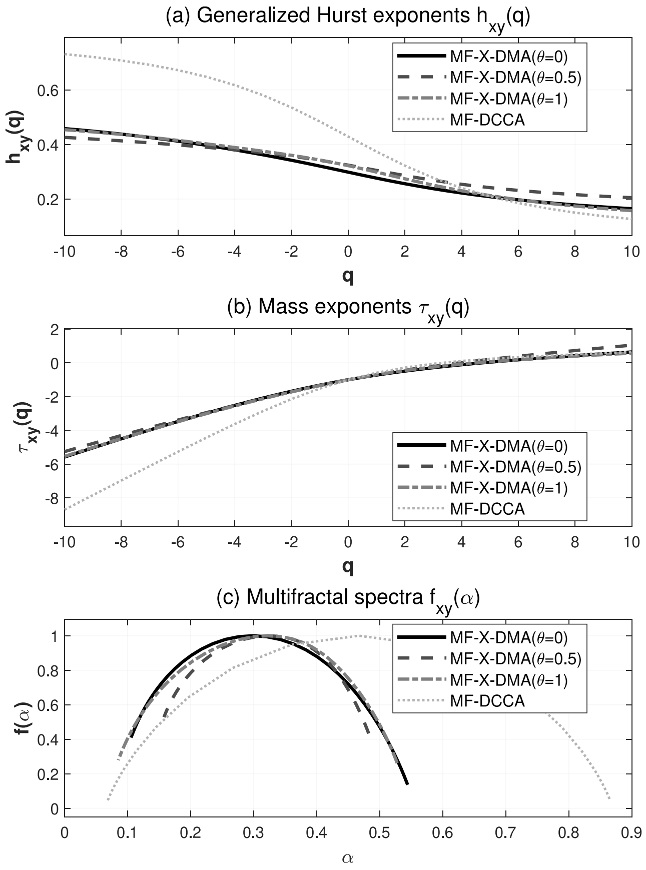


Fig. 17. Robustness analysis for the Hong Kong market (SB flows and HSI returns). Panel (a) shows the generalized Hurst exponents $h_{xy}(q)$, panel (b) presents the mass exponents $\tau_{xy}(q)$, and panel (c) reports the multifractal spectra $f_{xy}(\alpha)$, obtained using MF-X-DMA ($\theta = 0, 0.5, 1$) and MF-DCCA methods.

interactions may operate differently across scales. While institutional features and market structure may play a role, the present empirical framework does not allow for direct identification of such mechanisms.

From a broader perspective, these findings contribute to the literature on financial integration by highlighting the importance of distinguishing between within-market scaling behavior and cross-market dependence. In particular, the results suggest that cross-market relationships may vary across regimes, rather than exhibiting a uniform pattern of dependence.

The observed narrowing of multifractal spectra in certain downturn periods suggests that the relationship between market stress and multifractal complexity may involve regime-dependent reversals, consistent with — but not fully captured by — the baseline theoretical intuition. While the interpretation based on heterogeneous and state-dependent capital adjustment is consistent with the empirical findings, alternative explanations cannot be ruled out. For example, common external shocks may simultaneously affect both capital flows and returns, contributing to the observed cross-correlations. In addition, institutional features — such as trading constraints or regulatory conditions — may influence flow dynamics independently of investor behavior. Furthermore, aggregation effects inherent in multifractal estimation may also affect the observed scaling patterns. Therefore, the proposed interpretations should be understood as plausible explanations rather than definitive causal relationships.

Importantly, the scale-dependent and asymmetric features documented in this study are directly related to the central research question. By examining how the interaction between capital flows and returns varies across fluctuation regimes, the multifractal framework provides a complementary perspective to conventional approaches. In particular, the results suggest that the relationship between flows and returns may differ across scales, rather than being fully captured by aggregate measures.

More broadly, these findings provide additional insights into how capital flow dynamics can be interpreted. Traditional approaches often focus on aggregate flow volumes or average correlations, implicitly assuming that the informational content of flows is captured at a single scale. In contrast, the multifractal framework indicates that flow–return interactions may vary across fluctuation magnitudes and market states, highlighting the importance of considering scale-dependent dynamics.

Finally, although a formal subperiod analysis is beyond the scope of this study, the main patterns appear to be broadly stable across different market phases within the sample period. In particular, multifractality and the associated asymmetries are observed across both relatively tranquil periods and episodes of market stress. This suggests that the documented patterns are not driven by a specific subsample, but reflect persistent statistical features of the data.

8. Conclusion and policy implications

This study investigates the multifractal and asymmetric properties of cross-border capital flows and stock market returns within the Mainland China–Hong Kong Stock Connect framework. By combining a heterogeneous-agent perspective with asymmetric MF-DFA and MF-DCCA methodologies, the analysis documents scale-dependent dynamics, directional asymmetry, and non-linear cross-market interactions across different market conditions.

A central finding of the study is the presence of a systematic contrast between price dynamics and capital flow behavior across market states. While stock returns tend to exhibit more compressed multifractal spectra during downward phases, capital flows and their cross-market interactions display broader spectra, indicating greater dispersion in scaling behavior. we summarize this empirical regularity as a form of structural inversion, understood as a descriptive characterization of how multifractal complexity differs between prices and capital flows across market states, rather than as evidence of a causal shift.

From an economic perspective, the results suggest that capital flows may carry state-dependent and scale-dependent informational content that is not fully captured by aggregate measures or conventional correlation-based approaches. In particular, the increased multifractal complexity observed during withdrawal phases is consistent with the idea that capital flow dynamics become more heterogeneous — and potentially more informative — under adverse market conditions. While the empirical framework does not establish causality, these patterns indicate that cross-border capital flows may serve as a useful signal of evolving market fragility within partially integrated financial systems.

The analysis also highlights systematic differences between Northbound and Southbound channels. The findings suggest that Northbound flows exhibit relatively more homogeneous scaling behavior at larger time scales, whereas Southbound flows display more persistent heterogeneity across regimes. These differences are consistent with the distinct investor compositions of the two channels, although the present framework does not allow for direct identification of underlying behavioral mechanisms.

From a policy perspective, the results suggest that incorporating scale-dependent perspectives into monitoring frameworks may provide additional insights beyond conventional indicators. In particular, tracking how flow–return interactions evolve across fluctuation magnitudes and market states may offer complementary information for assessing systemic risk and market stability. The observed asymmetries between inflow and outflow regimes further indicate that withdrawal phases may warrant closer attention in regulatory analysis.

Several limitations should be acknowledged. First, the multifractal framework provides a descriptive characterization of scaling properties and does not uniquely identify underlying economic mechanisms. Second, the observed patterns may reflect a combination of temporal dependence, distributional features, and aggregation effects. Third, the analysis is conducted within the institutional context of the Stock Connect system, and caution is required when generalizing the findings to other financial markets. Overall, this study contributes to the literature by providing a scale-dependent perspective on the interaction between capital flows and market dynamics. By showing that the informational role of capital flows varies across market states and fluctuation magnitudes, the findings complement existing approaches based on aggregate flows and average correlations, and highlight the importance of considering multi-scale dynamics in the analysis of financial integration and systemic risk.

CRediT authorship contribution statement

Can-Zhong Yao: Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Hao Jiang:** Validation, Software.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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Dr. Can-Zhong Yao is a Professor at South China University of Technology. His research interests include financial risk, decision-making, complex networks, platform economics, industrial economics, and financial economics.

Hao Jiang is a bachelor's and master's student in Applied Economics at South China University of Technology, under the supervision of Professor Can-Zhong Yao. Her research interests focus on financial risk analysis, fintech applications, and complex network modeling in financial markets.